Systematic errors in calibration are important, and must be dealt with, either by working to eliminate them, or by providing people with means to deal with them: these are the two main goals of this WG.
Schedule

• Mar 1, WG meeting, 9:00am-10:45am IST
  • Intro to WG and pyBLoCXS, Vinay Kashyap
  • Intro to Cal Concordance, Herman Marshall
  • Updates to XSPEC, Keith Arnaud [skype]
  • Status of Cal Concordance Project, Yang Chen/Xufe Wang/Xiao-Li Meng [skype]
  • Discussion

• Mar 2, Improving Cross-Calibration Status, 9:45am-12:45pm IST
  • Monte Carlo constraints on instrument calibration, Jeremy Drake
  • NuSTAR and PyBlocks, Kristin Madsen [skype]
  • Panel Discussion: what next?
Calibration has Uncertainties

• The fundamental equation of observational astronomy

\[ C(i,j,k_1,k_2,t_f,\Delta t;\theta) = \int dt \int dxdy \int dE \cdot f(x,y,E,t;\theta) \]

\[ R(t,t_f) \text{ PSF}(x,y,E;t) \text{ RMF}(E,k;x,y,t) \text{ ARF}(E;x,y,t) \]

• Calibration analysis inverts the usual analysis method

• Given ARF, RMF, PSF, evaluate expected model spectrum to compare with observed counts

• Given known model spectrum, compare with observed counts to evaluate ARF, RMF, PSF
Calibration has Uncertainties

• How to find the uncertainties?

• Once known, how to account for them?

• And then how to minimize them?
Calibration has Uncertainties

• How to find and tabulate the uncertainties?
  • MCCal

• Once known, how to account for them?
  • pyBLoCXS

• And then how to minimize them?
  • Concordance
MCMC scheme to incorporate defined calibration uncertainty into analysis

Simulated = Nominal + Bias + randomized components + residuals
fitting to simulated data

\[ f(\varepsilon; \theta) = \theta_3 \varepsilon^{-\theta_1} e^{-\theta_2} \sigma(\varepsilon) \]
fitting to simulated data
\[ f(\varepsilon; \theta) = \theta_3 \varepsilon^{-\theta_1} e^{-\theta_2} \sigma(\varepsilon) \]

\[ p(\theta|D,A_0) \]
fitting to simulated data

\[ f(\varepsilon; \theta) = \theta_3 \varepsilon^{-\theta_1} e^{-\theta_2} \sigma(\varepsilon) \]

\[ p(\theta|D,A_0) \]

\[ p(\theta|D,A_i) \]
f(\varepsilon; \theta) = \theta_3 \varepsilon^{-\theta_1} e^{-\theta_2} \sigma(\varepsilon)

\begin{align*}
p(\theta|D,A_0) & \quad p(A) \ p(\theta|D,A) \\
p(\theta|D,A_i) & \quad p(\theta|D,A_i)
\end{align*}
fitting to simulated data
\[ f(\varepsilon; \theta) = \theta_3 \varepsilon^{-\theta_1} e^{-\theta_2} \sigma(\varepsilon) \]

- **Default Effective Area**
- **Pragmatic Bayes**
- **Fully Bayes**

\[
p(\theta|D,A_0) \quad p(A) \ p(\theta|D,A) \quad p(A,\theta|D)
\]

\[
p(\theta|D,A_i)
\]

— Jin Xu and Shandong Min
fitting to simulated data

\[ f(\varepsilon; \theta) = \theta_3 \varepsilon^{-\theta_1} e^{-\theta_2 \sigma(\varepsilon)} \]

- Jin Xu and Shandong Min
pyBLoCXS resources


• Sherpa (PragBayes): http://cxc.harvard.edu/sherpa/ahelp/pyblocxs.html

• github (FullBayes): https://github.com/astrostat/pyblocxs

• tutorial from IACHEC 2014: http://hea-www.harvard.edu/AstroStat/Demo/pyBLoCXS/IACHEC2014/